GreenAg: A Mobile Platform for Preservation and use of Eco-friendly Traditional Vegetable Crop Remedies in Sri Lanka

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ABSTRACT
At present, most Sri Lankans do not know the eco-friendly remedies for traditional vegetable crop diseases. The purpose of this is to provide a solution for that. Using advanced techniques of NLP, Convolutional Neural Networks, Image Processing and Deep Learning, GreenAg mobile application promotes eco-friendly vegetable crop remedy conservation and traditional vegetable crop remedies in Sri Lanka. This research demonstrates the effectiveness of this application and highlights the potential to revolutionize disease management, promote sustainable practices and ensure vegetable crop safety. This eco-friendly vegetable crop remedy conservation and disease management model offers a transformative solution for sustainable vegetable crop production. It not only addresses the complexities of disease management, but also links traditional knowledge with modern technology to empower farmers and control diseases in vegetable crops.

Keywords
Model, Machine Learning, Convolutional Neural Networks, Natural Language Processing, Artificial Intelligence, Chatbot, Deep Learning, Image Processing, Agriculture, Traditional Remedy

1. INTRODUCTION
With a rich history in agriculture, the use of traditional remedies to combat pests and diseases affecting vegetable crops in Sri Lanka has a long history. Although these treatments have proven to be effective, their use has declined as a result of the use of modern chemical pesticides and fertilizers, as shown in Fig 1. However, the implementation of traditional treatment methods is beneficial to the environment and the public as well as no harm to health [1]. Over time, knowledge of these therapies was passed down orally from generation to generation, leading to the extinction of many valuable methods. Widespread adoption of contemporary synthetic and chemical practices in agriculture has further reduced conventional treatments, and also causes significant environmental damage, including soil erosion and water pollution [2], [3].

The transition to modern agricultural practices has posed challenges for both family heirloom farmers and new entrants to the industry. Lack of understanding of traditional eco-friendly treatments is a concern. Farmer parents have failed to impart knowledge to their children, especially regarding the cultivation of vegetable crops. Moreover, as later generations move on to other occupations, the knowledge of traditional farmers is lost. These issues extend beyond farmers to people who grow vegetables in their backyards. Such people often lack extensive cultivation experience and turn to external resources such as books and articles for crop cultivation knowledge. However, the reliability and relevance of such information remains uncertain, leading to ineffective solutions or outdated practices [4]. Although some traditional treatments are documented in manuscripts, those sources are more likely to be inaccurate.

To meet these challenges, it is necessary to preserve traditional methods of treatment and provide contemporary technology to farmers and individuals by promoting eco-friendly cultivation practices. An integrated system using modern technology is essential to provide comprehensive support against vegetable crop diseases through effective management strategies [5]. Integrating an app that empowers farmers and individuals to make informed decisions while preserving the valuable heritage of traditional techniques has the potential to improve sustainable vegetable farming practices.

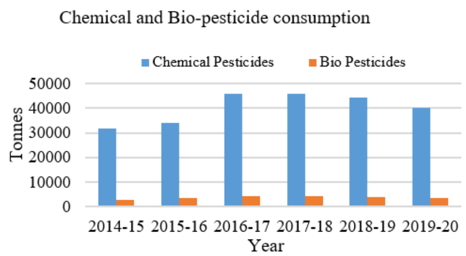


Fig 1: Chemical and Bio-pesticide consumption

2. LITERATURE REVIEW

PEAT GmbH's Plantix app demonstrates the impact of digital technology on agriculture, using AI and image recognition to manage plant diseases. It assists farmers in disease detection and provides crop management recommendations based on plant images. However, real-world effectiveness may vary due to factors such as image quality and disease type. Plantix offers weather data and growth stages but lacks features like GreenAg app existing chatbot-based observation collection, individual disease detection from user inputs, and severity rate predictions. Therefore, this new application offers a comprehensive approach to disease management, integration of user interaction, AI Chatbots, and data-driven insights to promote sustainable agriculture [6].

Agrio, an innovative smartphone application [7], uses image recognition technology to accurately identify 400+ crop diseases and pests with a 90% accuracy rate. It uses deep learning for rapid analysis and provides insight into crop nutrition and pest management. GreenAg app is at the forefront with multi-disease detection, Chatbot-based monitoring, and more comprehensive crop health management features [8].

PictureThis app uses picture recognition technology for plant identification, providing details on plant names, species, and care instructions for 10,000+ species with 98% accuracy. It provides gardeners but lacks features like the advanced interaction provided by the GreenAg app for disease detection and holistic crop health management [8].

PlantSnap, a smartphone application, has a database of more than 600,000 plant species and uses image recognition to identify plants. It provides reliable identification with an estimated 92% accuracy rate. However, it lacks features like disease detection, severity prediction and AI Chatbot interaction for user authentication data collection, which are essential components of GreenAg for comprehensive crop health management. PlantSnap is great for identifying plants and fostering botanical curiosity, making it a valuable tool for plant lovers to explore nature [9].

Crop Doctor, a mobile application, helps farmers by identifying crop diseases and pests through image recognition. It provides detailed insights and treatment recommendations. It provides valuable features such as weather data and soil analysis, and by GreenAg including multiple disease detection, chatbot-based monitoring, individual disease detection through user inputs, severity rate prediction, and AI Chatbot-based user verification data collection. Crop Doctor is user-friendly but different from the holistic crop health management of the GreenAg app [10].

Artificial intelligence plays an important role in modern agriculture. In particular, it protects crops from the devastating effects of plant diseases that affect both crop and human health. Smartphone-assisted disease detection, facilitated by deep learning algorithms and computer vision technology, provides improved accuracy in identifying diseased leaves. GreenAg is an innovative project that expands those solutions and adds new solutions. GreenAg application revolutionizes plant disease management [11].

This highlights the growing interest in deep learning, a subset of artificial intelligence, and its applications across industries including agricultural crop protection [12]. The prowess of deep learning in feature extraction and automatic learning, especially in image processing and disease detection, is well documented. However, the review will not go into the GreenAg-specific platform that offers a comprehensive solution for plant disease management, recommendations, and user engagement. The GreenAg app stands out with its unique features such as user input to select the affected plant part and addressing different diseases in different plant parts.

Identifying plant diseases highlights the potential of artificial intelligence, particularly deep learning, to enhance crop productivity and food security. Convolutional Neural Network (CNN) successfully detects tomato diseases with more than 91.66% accuracy but primarily focuses on disease detection [13]. But, the GreenAg app offers a comprehensive platform with disease detection, recommendations, user interaction and remedies for various crop diseases, providing a comprehensive solution for sustainable agriculture.

The literature discusses the use of Convolutional Neural Networks (CNN) in early identification of diseases like Early Blight and Late Blight in Indian potato crops. Achieving 99% accuracy in disease categorization, the focus is on disease identification and classification. In contrast, GreenAg offers a holistic platform covering multiple aspects of crop health management, including detection, suggestions, user interactions, and remedies for various plant diseases affecting diverse crops, providing a more comprehensive approach to sustainable agriculture [14].

The literature review underscores the importance of addressing plant diseases in India due to their significant impact on agriculture and food supply. It proposes a method using convolutional neural networks and the Inception V3 model for disease classification. In contrast, GreenAg offers a holistic solution, including disease identification, treatment suggestions, and user interaction, promoting agricultural sustainability and reducing pesticide dependency. GreenAg stands out as a comprehensive, user-centric approach to crop disease management and sustainable agriculture [15].

3. METHODOLOGY

GreenAg is a farmer-tailored app utilizing advanced technologies like NLP, image processing, and deep learning for plant disease management. It comprises the Eco-Friendly Remedy Preserving Model (EFRP) for accurate prescription through NLP and deep learning. The Vegetable Crop Disease Tracking Model (VCDT) detects diseases through image processing, while the Vegetable Crop Disease Verification Model (VCDV) uses vegetable crop disease observations and AI Chatbot interactions. The Vegetable Crop Disease Severity and Risk Management Prediction (VCDSRMP) model predicts disease severity using a blend of image processing, deep learning, and NLP. This comprehensive approach, depicted in Fig 2, ensures accurate disease management, risk prediction, and sustainable agriculture.

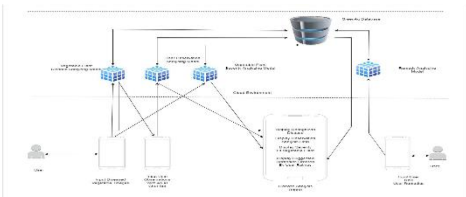


Fig 2: Overall system diagram

3.1 GreenAg Eco Friendly Remedy preserving Model (GreenAg EFRP Model)

This section presents a detailed methodology for the development, training, and evaluation of the Multinomial

Naive Bayes Classifier model, which forms the core of our research for the classification of home remedies.

3.1.1 Data Acquisition and Preprocessing

The cornerstone of this research is a comprehensive dataset meticulously collected from [Dataset Source]. This dataset consists of [Number of Instances] instances, where each instance comprises textual descriptions of home remedies along with their corresponding class labels. To ensure data quality and model effectiveness, a series of preprocessing steps were undertaken.

3.1.2 Data Preprocessing Steps

Irrelevant characters, special symbols, and non-essential textual elements were removed from the dataset. Textual data was tokenized into individual terms, preparing it for further analysis. The dataset was partitioned into training and testing subsets to enable model development and evaluation, with a [Splitting Method] approach determining the division. Approximately 82% of the dataset was designated for model training, while the remaining 75% was reserved for assessing model performance.

3.1.2.1 Feature Extraction - TF-IDF Representation

To transform the textual data into a format suitable for machine learning, a feature extraction technique was employed. This involved the creation of a Term Frequency-Inverse Document Frequency (TF-IDF) matrix, calculated for each term in the dataset. The TF-IDF value for a term t in a document dd is computed as:

$$\text{TF-IDF}(t,d)=\text{TF}(t,d)\times\text{IDF}(t)$$

3.1.2.2 Model Definition - Multinomial Naive Bayes Classifier

The core of our classification approach is the Multinomial Naive Bayes Classifier. This classifier operates by estimating the probability that a document dd belongs to a class cc using Bayes' theorem. The probability is computed as follows:

$$P(c \mid d) \propto P(c)\prod i = 1nP(ti \mid c)fiP(c \mid d) \propto P(c)\prod i = 1nP(ti \mid c)fi$$

3.1.2.3 Model Training and Evaluation

The re-trainable Multinomial Naive Bayes model was trained iteratively using an incremental learning approach. For each training instance, the model underwent incremental updates to enhance its classification accuracy. Training continued until a satisfactory level of model performance was achieved.

3.1.2.4 Model Evaluation Metrics

The trained Multinomial Naive Bayes Classifier was evaluated using various performance metrics, with a primary focus on accuracy. Accuracy, in the context of this research, measures the proportion of correctly predicted labels in the testing subset.

3.2 GreenAg Vegetable crop Disease Tracing Model (GreenAg VCDT Model)

3.2.1 Data Acquisition and Preprocessing

The dataset utilized in this study was sourced from database comprising images distributed across distinct classes. A thorough data preprocessing phase was undertaken to ensure data quality and model effectiveness. The dataset was partitioned into training and testing subsets to facilitate model training and evaluation.

3.2.2 Data Augmentation

To enhance the model's generalization capabilities, data augmentation techniques were employed during the training process. The ImageDataGenerator class was utilized to apply essential transformations such as rescaling, shearing, zooming, and horizontal flipping to the training data.

3.2.3 Convolutional Neural Network Architecture

The Convolutional Neural Network (CNN) architecture chosen for this study was carefully designed to suit the task of multi-class classification. The architecture includes a series of convolutional layers followed by max-pooling layers for feature extraction. The key equations employed in the architecture are as follows:

3.2.3.1 Squared Hinge Loss Equation

Squared hinge loss, a popular choice for multi-class classification, is used in this study to compute the loss for each data point. The squared hinge loss for a single data point is defined as:

$$L_{squared\ hinge}\big(y, f(x)\big) = \frac{1}{2}\max\,(0{,}1 - y \cdot f(x))^2$$

3.2.3.2 softmax Activation Equation

The softmax activation function transforms raw scores into class probabilities. The softmax function for the ith class is given by:

$$P(y_i|x) = \frac{e^{f_{i}(x)}}{\sum_{j=1}^{k} e^{f_{j}(x)}}$$

3.2.4 Model Compilation and Training

The CNN model was compiled using the Adam optimizer and the squared hinge loss function. It was trained over a specified number of epochs while monitoring its performance on both the training and validation sets. The regularization technique employed in the output layer is L2 regularization, which helps mitigate overfitting.

3.3 GreenAg Vegetable crop Disease Verification Model (GreenAg VCDV Model)

3.3.1 Data Collection and Preprocessing

The first step entailed gathering observation data concerning diseases in vegetable crops. This data was organized in a structured format, with disease names paired with their respective observations. To prepare the data for training and assessment, extracted and preprocessed the textual observations. This preprocessing involved generating various permutations of observation sequences, thereby improving the model's capacity to comprehend diverse contexts.

3.3.2 Convolutional Neural Network Architecture

The core architecture of the VCDV Model is based on Convolutional Neural Networks (CNNs). This architecture was chosen due to its effectiveness in processing sequential data and its ability to capture relevant features from short-text observations. The model consists of an embedding layer, followed by a Global Average Pooling layer to reduce dimensionality, and fully connected layers for classification.

3.3.3 Equations Underpinning Sequential Short-Text Classification

Integral to the development of the VCDV Model, a pivotal phase involves the utilization of mathematical expressions to shape the sequential short-text classification methodology. The Convolutional Neural Network (CNN) leverages these equations to perform intricate transformations, ensuring the effective extraction of relevant features from the input observations.

3.3.3.1 Historical Context Extraction

In this equation, the first layer of the CNN extracts historical context from the sequence of short-text representations. This context is then employed to formulate the sequence of class representations:

$$y_j = \tanh\left(\sum_{d=0}^{d_1} W_{-d} s_{j-d} + b_1\right), \forall j \in [i - d_{2,} i]$$

3.3.3.2 Class Label Prediction

Subsequently, the second layer of the CNN applies the following equation to the sequence of class representations, yielding the definitive probability distribution across disease classes:

$$z_i = softmax\left(\sum_{j=0}^{d_2} W_{-j} y_{i-j} + b_2\right)$$

3.3.4 Model Compilation and Training

Prior to training, data was divided into training and testing sets. The training set facilitated model training, while the testing set assessed its performance. Text observations underwent tokenization and conversion to numerical sequences, with padding for uniformity. The model was compiled using categorical cross-entropy loss and the Adam optimizer. Training utilized early stopping and learning rate reduction callbacks to prevent overfitting and enhance convergence.

3.4 GreenAg Vegetable crop Disease Severity & Risk Management Prediction Model (GreenAg VCDSRMP Model)

This section outlines the comprehensive methodology employed in the development, training, and evaluation of the Convolutional Neural Network (CNN) model for the task of image classification. The methodology encompasses crucial steps such as data preprocessing, model architecture design, training configuration, and evaluation metrics.

3.4.1 Data Preprocessing

A vital initial stage involves the preprocessing of the dataset, ensuring its alignment with the training process. Leveraging the capabilities of the ImageDataGenerator module from TensorFlow's Keras library, applied diverse augmentation techniques to both the training and test datasets.

For pixel value rescaling, the equation below was applied to normalize the pixel values to the range [0, 1]:

$$Rescaled\_Pixel\_Value = \frac{Original\_Pixel\_Value}{255}$$

Shear transformations, integral for enriching dataset diversity, were implemented through the equations:

$$x' = x + shear_{range} \times y$$

$$y' = y$$

Zooming transformations, enriching scale variations, were effectuated using the equation:

$$Zoomed\_Pixel\_Value = Original\_Pixel\_value \times zoom\_range$$

3.4.2 Model Architecture Design

The architecture of the CNN was meticulously crafted to hierarchically extract intricate features from input images. Realized using Keras' Sequential API, the architecture encompasses convolutional, pooling, and fully connected layers. The convolutional layers, activated by the Rectified Linear Unit (ReLU) function, harnessed the following equation to compute feature maps:

$$\text{Feature\_Map}_{i,j} = \sum_{m=1}^{M} \sum_{n=1}^{N} Image_{i+m,j+n} \times Kernel_{m,n}$$

The process of spatial dimension reduction was facilitated by the introduction of max pooling layers, governed by the equation:

$$Pooled\_Value_{i,j} = max_{m=1}^{M} max_{n=1}^{N} Feature\_Map_{i \times M+m, j \times N+n}$$

3.4.3 Training Configuration

The CNN model was trained through the utilization of the fit function. Employing the Adam optimizer as the cornerstone of gradient descent, the squared hinge loss function was chosen due to its efficacy in the context of multiclass classification tasks.

3.4.4 Evaluation Metrics

Evaluation of the model's performance was conducted employing essential metrics including accuracy and loss. The accuracy metric, quantified by the equation:

$$\text{Accuracy} = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}$$

The loss metric was calculated using the squared hinge loss equation:

$$\text{Loss} = \frac{1}{N} \sum_{i=1}^{N} \max(0, 1 - y_i \cdot \hat{y}_i)^2$$

4. DATA ANALYSIS

4.1 GreenAg Eco Friendly Remedy preserving Model (GreenAg EFRP Model)

Data analysis of the EFRP model included several steps to ensure robustness. NLP and Deep Learning algorithms processed the data, and pre-processing techniques removed inconsistencies and irrelevant data. Quality control resulted in the exclusion of erroneous data points. The model was continuously improved through a retraining approach, updating existing models with new remedies. During training, errors were addressed through feedback and validation, resulting in improved iterative performance.

4.2 GreenAg Vegetable crop Disease Tracing Model (GreenAg VCDT Model)

Data analysis in the VCDT model involved the collection of vegetable crop images (flowers, leaves, stems). Preprocessing included resizing, normalization, and noise reduction, along with removing blurry or low-quality images. The model was trained by deep learning to identify disease patterns, addressing errors such as false positives/negatives through overfitting, varying training data, and fine-tuning. Ongoing validation and real-world testing improved model accuracy.

4.3 GreenAg Vegetable crop Disease Verification Model (GreenAg VCDV Model)

Data analysis of VCDV format collected user observations using NLP and Deep Learning. Preprocessing included tokenization and sentiment analysis, excluding irrelevant or incomplete data. The found observation data and AI Chatbot verified suspected diseases with user inputs but encountered misinterpretation and misclassification errors. Continuous training refined the found vegetable crop disease observation data, the Chatbot's question generation and responses based on user feedback, improving accuracy over time.

4.4 GreenAg Vegetable crop Disease Severity & Risk Management Prediction Model (GreenAg VCDSRMP Model)

Data analysis of the VCDSRMP model used vegetable crop images and user verification data with preprocessing including normalization, data augmentation, and feature extraction. Outliers and inconsistencies led to the removal of some data points. The training used image processing, deep learning, and NLP techniques, but encountered overfitting and underfitting errors. These are mitigated by adjustments in model architecture, regularization, and overhead. Continuous validation and cross-validation were performed to assess and improve the predictive performance of the model.

5. RESULTS AND DISCUSSION

5.1 GreenAg Eco Friendly Remedy preserving Model (GreenAg EFRP Model)

In Fig 3, which shows the distribution of traditional remedies associated with each illness class in the training set, sheds light on the make-up and balance of the dataset. Each bar's height reflects how many treatments are available for that illness class.

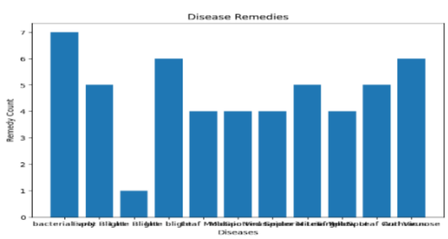


Fig 3: Remedy count

Fig 4 illustrates disease and traditional remedy accuracy, giving important details about how well the model performed on this dataset.

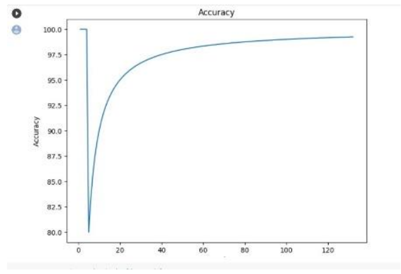


Fig 4: Accuracy

5.2 GreenAg Vegetable crop Disease Tracing Model (GreenAg VCDT Model)

The output, which is displayed as a bar chart, shows the distribution of different illness classifications within the training dataset. The height of each bar in the graphic represents the number of disease images linked with that specific disease class in the training dataset, and each bar represents a different disease category. This visualization enables a thorough comprehension of the dataset's composition and balance by providing insightful information about the distribution of data across various plant disease kinds. Referring to Fig 5 will provide further details.

Fig 5: Disease images count

Fig 6 clearly shows the performance of the GreenAg Disease Image Classification Model. The model exhibits strong learning skills, suggesting its usefulness in reliably classifying vegetable crop illnesses across a variety of datasets, with a training accuracy of 78% and validation accuracy of 75%. This high level of accuracy indicates the model's potential for use in agricultural situations in the real world.

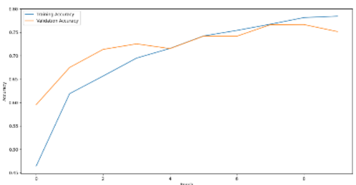
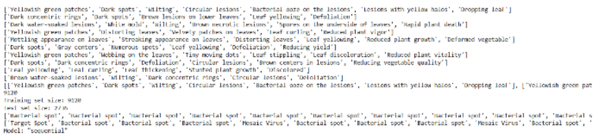


Fig 6: Accuracy

5.3 GreenAg Vegetable crop Disease Verification Model (GreenAg VCDV Model)

The output includes a list of disease observations associated with various plant diseases. The list is divided into sections, each of which relates to a particular condition and provides information on its observations or other features. In agricultural or gardening contexts, this knowledge can be used as a reference for recognizing and diagnosing plant diseases based on observable symptoms. Consult Fig 7 for more clarification.



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['Yellowish green patches', 'Dark spots', 'Wilting', 'Circular lesions', 'Bacterial ooze on the lesions', 'Lesions with yellow halos', 'Dropping leaf']
['Dark concentric rings', 'Dark spots', 'Brown lesions on lower leaves', 'Leaf yellowing', 'Defoliation']
['Dark water-soaked lesions', 'White mold', 'Wilting', 'Brown necrotic lesions', 'Spores on the underside of leaves', 'Rapid plant death']
['Yellowish green patches', 'Distorting leaves', 'Velvety patches on leaves', 'Leaf curling', 'Reduced plant vigor']
['Mottling appearance on leaves', 'Streaking appearance on leaves', 'Distorting leaves', 'Leaf yellowing', 'Reduced plant growth', 'Deformed vegetable']
['Dark spots', 'Gray centers', 'Numerous spots', 'Leaf yellowing', 'Defoliation', 'Reducing yield']
['Yellowish green patches', 'Webbing on the leaves', 'Tiny moving dots', 'Leaf stippling', 'Leaf discoloration', 'Reduced plant vitality']
['Dark spots', 'Dark concentric rings', 'Defoliation', 'Circular lesions', 'Brown centers in lesions', 'Reducing vegetable quality']
['Leaf yellowing', 'Leaf curling', 'Leaf thickening', 'Stunted plant growth', 'Discolored']
['Brown water-soaked lesions', 'Wilting', 'Dark concentric rings', 'Circular lesions', 'Defoliation']
[['Yellowish green patches', 'Dark spots', 'Wilting', 'Circular lesions', 'Bacterial ooze on the lesions', 'Lesions with yellow halos', 'Dropping leaf'], ['Yellowish green pat
9120
Training set size: 9120
Test set size: 2736
['Bacterial spot', 'Bacterial spot', 'Bacterial spot', 'Bacterial spot', 'Bacterial spot', 'Bacterial spot', 'Bacterial spot', 'Bacterial spot', 'Bacterial spot', 'Bacterial s
['Target Spot', 'Bacterial spot', 'Bacterial spot', 'Bacterial spot', 'Mosaic Virus', 'Bacterial spot', 'Bacterial spot', 'Bacterial spot', 'Mosaic Virus', 'Bacterial spot', '
Model: "sequential"
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Fig 7: Observations

The model achieves a test accuracy of 78.95%, which is remarkable Fig 8. This demonstrates its competence in precisely diagnosing and identifying vegetable crop diseases, constituting an important advancement in our research efforts.

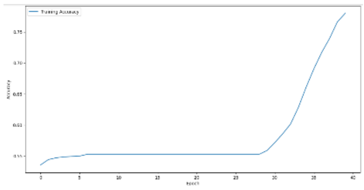

Fig 8: Accuracy

5.4 GreenAg Vegetable crop Disease Severity & Risk Management Prediction Model (GreenAg VCDSRMP Model)

The distribution of different vegetable crop types in the training dataset is shown in Fig 9. The number of healthy images in each class is represented by the height of each bar, providing information on the dataset balance.

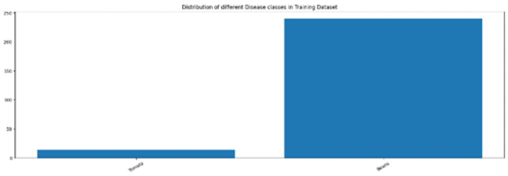

Fig 9: Healthy images count

Fig 10 illustrates the model's remarkable performance during validation rounds. The model exhibits strong learning capabilities, exhibiting its efficiency in classifying vegetable crop illnesses across a variety of datasets with a validation accuracy of 78.4%.

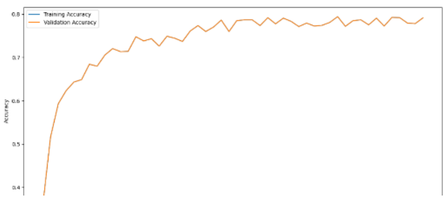

Fig 10: Accuracy

The study discovered significant constraints affecting the effectiveness of machine learning and data analysis in app components. Misclassifications were caused by inconsistent data and inaccurate user inputs, which had an impact on model outputs. Strict data quality control procedures, including meticulous validation of user inputs and observations, are required to address these concerns. Accuracy can be improved by enhancing model fine-tuning, real-time user feedback, and false positive/negative reduction. Through trustworthy disease management suggestions, GreenAg helps farmers, consultants, and agricultural institutions increase crop output. Environmentally friendly behaviors can be encouraged by policymakers, minimizing environmental effects.

Future research should focus on obtaining diverse datasets, incorporating regional factors, and using advanced techniques such as state-of-the-art NLP algorithms and deep learning architectures to improve accuracy. User interaction enhancements, guided queries, and real-time feedback mechanisms can improve user monitoring and remediation details.

6. CONCLUSION

GreenAg is revolutionizing crop management using cutting edge technology like NLP, Deep Learning, and AI Chatbots. In terms of disease detection, confirmation, severity prediction, and risk management, its components are excellent. GreenAg fills in the gaps in current methods by fusing user observations with sustainable practices. The study emphasizes the opportunity for customized, environmentally friendly agricultural cultivation advice.

This research embodies an important step towards sustainable agriculture. It provides a reliable means of combating plant diseases, managing risks, and mitigating crop diseases. The research underscores the importance of leveraging advanced technologies to improve productivity and economic viability. A recommendation to refine and validate components of the research, including real-world trials and user feedback. Expanding GreenAg app capabilities to cover more crop types and regions will improve its versatility. Continuous collaboration with experts is essential to evolve research and adapt it to agricultural needs. Ultimately, this research has the potential to significantly advance sustainable agricultural practices and global crop management strategies.

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